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Original Article

The Subjective Dynamic Decision Model (SDEM): A New Approach to Decision-Making Under Radical Uncertainty

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ABSTRACT

This paper develops a hybrid model for strategic decision-making in contexts of radical uncertainty. It combines the formal structure of game Theory with the epistemological principles of the Austrian School of Economics. The Subjective Dynamic Decision Model (SDEM) describes decisions not as the result of rational optimisation, but as the result of subjective perception, heuristic action strategies and iterative learning processes. The focus is on modelling the subjective decision-making state, consisting of information, conviction and expectation. Decisions arise from this through experience-based heuristics and are modified by observed results. In addition to the theoretical derivation, the article also provides concrete applications in the areas of cyber security, market behaviour and intelligence work. Simulation-based analyses are used to show how adaptive decision-making strategies develop in complex environments. While generalisability to real-world settings may be limited due to reliance on simulation, SDEM enables practical scenario modelling in volatile domains where traditional optimisation fails. The aim is not to describe optimal solutions, but to analyse subjective adaptation processes in non-linear decision-making contexts. The model thus stands for an insight-oriented approach to decision research.

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INTRODUCTION

Simple models of dynamic decision-making fail to capture how real actors decide under radical uncertainty. Most models, ranging from standard subjective expected utility models (Klibanoff et al., 2005; He, 2021) to recent subjective dynamic decision models (He, 2024; Sin et al., 2021; Georgalos, 2021), assume rational expectations, objective probabilities, and recursive optimisation assumptions that are largely invalid in dispersed, ambiguous settings (Hayek, 1945; Simon, 1955; Etner et al., 2010). In these environments, decision-makers face not only information gaps but also epistemic constraints that hinder precise probability assignments or optimization-based reasoning.

This growing critique motivates the need for a new approach reflecting the subjective, limited, and flexible character of actual decision-making. The Subjective Dynamic Decision Model (SDEM) responds to this need. Rather than relying on idealised rationality, SDEM explicitly models the decision-maker's internal state—composed of interpreted signals, personal convictions, and expectations—and emphasizes how decisions emerge from heuristics shaped by experience. It builds on empirical findings showing that individuals form non-rational beliefs (An et al., 2020; Georgalos, 2021), use idiosyncratic value functions in sequential tasks (Sin et al., 2021), and respond to ambiguity in heterogeneous ways (Ma et al., 2017; Sarin & Winkler, 1992).

Unlike dynamic programming models based on Bayesian foresight (He, 2024), SDEM conceptualises agents as short-sighted learners who iteratively revise their beliefs in response to perceived signals. Drawing on Simon's (1955) notion of satisficing and Hayek's (1945) view of dispersed knowledge, the model treats agents as having limited cognitive capacity, fragmented information, and evolving aspirations. The resulting subjective decision state enables action without requiring optimisation, while feedback loops allow for adaptation, learning from shocks, and the emergence of behavioural regularities—features that classical models often fail to accommodate (Fox et al., 2013; Moch, 2025).

Formal model structure

Decision-makers under radical uncertainty must operate through subjective perception, heuristic techniques, and adaptive learning (Gilbert-Saad et al., 2023; Kurdoglu et al., 2022) rather than depending on objective optimization. The Subjective Dynamic Decision Model (SDEM) formalizes the changing subjective state of the decision-maker, therefore capturing this process.

A decision-maker **i** is in a subjective decision-making state at any time **t** S_t^i, which is made up of

$$S_t^i = (I_t^i, B_t^i, E_t^i)$$

In this context, I_t^i refers to available information, B_t^i to beliefs and E_t^i to subjective expectations about future events or conditions.

The decision in period t results from a heuristic function (Gigerenzer & Selten, 2002):

$$a_t^i = D^i(S_t^i)$$

The decision rule D^i is not to be understood as an optimisation rule, but as a cognitive mechanism that leads to an action on the basis of experience, routines and intuition. Unlike optimisation, which aims to determine the mathematically best choice by evaluating all alternatives, a heuristic function simplifies decision-making by applying rules of thumb derived from past experience, contextual cues, or intuition.

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A simple example of a heuristic is (Gigerenzer & Selten, 2002):

$$D^i(S_t^i) = \begin{cases} \text{handle}, & \text{wenn } E_t^i[u(a)] > \theta \\ \text{warte}, & \text{sonst} \end{cases}$$

In this context, θ denotes an individual expectation threshold for the subjectively expected benefit. $E_t^i[u(a)]$

After observing a result, the decision status is adjusted:

$$S_{t+1}^i = U^i(S_t^i, a_t^i, o_t^i)$$

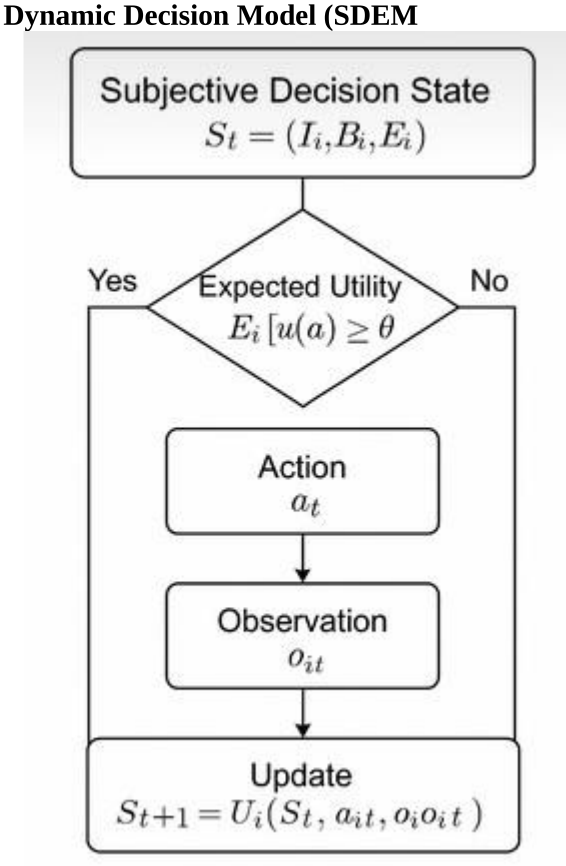
The update function U^i describes how actors adapt their state based on their subjective interpretation of the environment. A simple form would be, for example, a moving expected value: $E_{t+1}^i = \alpha \cdot o_t^i + (1 - \alpha) \cdot E_t^i$. Here α stands for the learning rate. This creates an iterative, subjective decision model based on perception, interpretation and experience. For example, consider a commuter who updates their preferred route to work based on traffic conditions from the previous day. If the route was fast, their expectation of it being efficient increases. If it was delayed, their expectation drops. This gradual adjustment process reflects the learning rule used in SDEM.

After observing a result o_t^i , the decision status is adjusted:

$$S_{t+1}^i = U^i(S_t^i, a_t^i, o_t^i)$$

The update function U^i describes how actors adapt their state based on their subjective interpretation of the environment. This can be formally understood as a learning process that also takes into account erroneous or distorted perceptions. This diagram of Figure 1 illustrates the states and actions in the Subjective Dynamic Decision Model (SDEM). An agent in state St, characterised by subjective information, beliefs and expectations of various alternatives (interpreted information), evaluates the expected utility of these alternatives relative to an individual utility threshold (θ). If the expected utility exceeds the threshold, the agent takes an action (αt); otherwise, it takes no action. Upon observing the outcome (o_{it}) following the last action, the agent updates the subjective decision state St+1 using the learning function U^i (which takes into account the feedback from the outcome and any perceptual distortions). How ideas and decisions evolve under extreme uncertainty.

Figure 1: Decision logic in the Subjective Dynamic Decision Model (SDEM



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The figure shows the decision-making flow of an actor in the SDEM. Source: Own illustration according to Enrico Moch (2025), based on the structure of the SDEM.

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METHODOLOGY

An agent-based simulation model was developed to test and exemplify the SDEM (Epstein, 2006; Tesfatsion & Judd, 2006). This model depicts the interactions of several decision-makers, each of whom has an individual subjective state. The simulation takes place in discrete time steps. At each point in time, each agent calculates a decision $a_t^i = D^i(S_t^i)$ based on its heuristic function, which uses the subjective decision state S_t^i as input. The decision-making environment then generates an observable result o_t^i that, in turn, leads to a modification of the decision state through the update function U^i. The update mechanism shows agents' changing expectations and beliefs in response to feedback. Both exact and distorted feedback are analysed. Distorted feedback was implemented by introducing noise to the observed outcome o_t^i, simulating perception errors or misinformation. This noise followed a normal distribution with zero mean and adjustable variance to represent different levels of perceptual distortion. Agents updated their expectations based on this potentially biased signal, which allowed the model to examine resilience and adaptation under incomplete or misleading feedback. Python was used for the simulation with numerical and probabilistic libraries. Systematic variations in learning rates (α), uncertainty parameters, and signal information were varied to explore the emergence of robust behavioural regularities and adaptive processes. The model was tested across varying agent population sizes to assess scalability. While moderate simulations ran efficiently on standard hardware (Intel i7, 16GB RAM), higher-scale runs required parallelization to maintain computational performance (Pan et al., 2018).

The model contributes to the study of subjective, iterative learning patterns in radical uncertainty. It extends simple learning approaches used in agent-based models to an explicit consideration of bounded rationality (Simon, 1955).

SIMULATION RESULTS

In a prototype application, two energy-producing players simulated their supply decisions over 50 periods in a volatile market environment. The initial expectations regarding price development differed, but were successively adjusted through feedback. The result shows that both actors were able to adjust their decisions more consistently to market dynamics through subjective learning. High initial uncertainty initially led to cautious behaviour, but later to divergent specialisations. The simulation demonstrates that SDEM is capable of modelling realistic learning curves and path dependencies in complex systems (Arthur, 1994; Epstein, 2006).

In-depth computational simulation: market behaviour of three subjective learning actors

To further illustrate the SDEM, a computer simulation is carried out below with three agents operating in a simple energy market. The aim is to show how decisions and expectations can change under uncertainty through subjective learning.

Initial situation

Three actors (A1, A2, A3) periodically make supply decisions based on subjective expectations of the market price. Each actor has an individual decision status $S_i^t = (U_i^t, B_i^t, E_i^t)$, whereby the expectation component E_i^t is particularly relevant here. A bid decision is made when the expected price development exceeds the individual threshold δ_i :

$$a_i^t = \begin{cases} \text{"handle"}, & \text{wenn } E_i^t > \delta_i \\ \text{"warte"}, & \text{sonst} \end{cases}$$

After each round, the agents adjust their expectations using the following learning rule:

$$E_i^{t+1} = \alpha_i \cdot E_i^t + (1 - \alpha_i) \cdot p^t$$

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Parameters:

Agent	Erwartung E_i^0	Schwelle δ_i	Lernrate α_i
A1	70	65	0,6
A2	60	62	0,5
A3	80	75	0,7

Period t = 0

- A1: 70 > 65 => handle
- A2: 60 < 62 => wait
- A3: 80 > 75 => handle

Market price: p^0 **= 68**

Expectation update:

$$E_1^1 = 0{,}6 \cdot 70 + 0{,}4 \cdot 68 = 69{,}2$$

$$E_2^1 = 0{,}5 \cdot 60 + 0{,}5 \cdot 68 = 64$$

$$E_3^1 = 0{,}7 \cdot 80 + 0{,}3 \cdot 68 = 76{,}4$$

Period t = 1

- A1: 69.2 > 65 => handle
- A2: 64 < 62 => handle
- A3: 76.4 > 75 => handle

Market price: p^1 **= 63**

Expectation update:

$$E_1^2 = 0{,}6 \cdot 69{,}2 + 0{,}4 \cdot 63 = 66{,}72$$

$$E_2^2 = 0{,}5 \cdot 64 + 0{,}5 \cdot 63 = 63$$

$$E_3^2 = 0{,}7 \cdot 76{,}4 + 0{,}3 \cdot 63 = 72{,}38$$

Period t = 2

- A1: 66.72 > 65 => handle
- A2: 63 > 62 => handle
- A3: 72.38 < 75 => wait

Market price: p^2 **= 66**

Expectation update:

$$E_1^3 = 0{,}6 \cdot 66{,}72 + 0{,}4 \cdot 66 = 66{,}43$$

$$E_2^3 = 0{,}5 \cdot 63 + 0{,}5 \cdot 66 = 64{,}5$$

$$E_3^3 = 0{,}7 \cdot 72{,}38 + 0{,}3 \cdot 66 = 70{,}47$$

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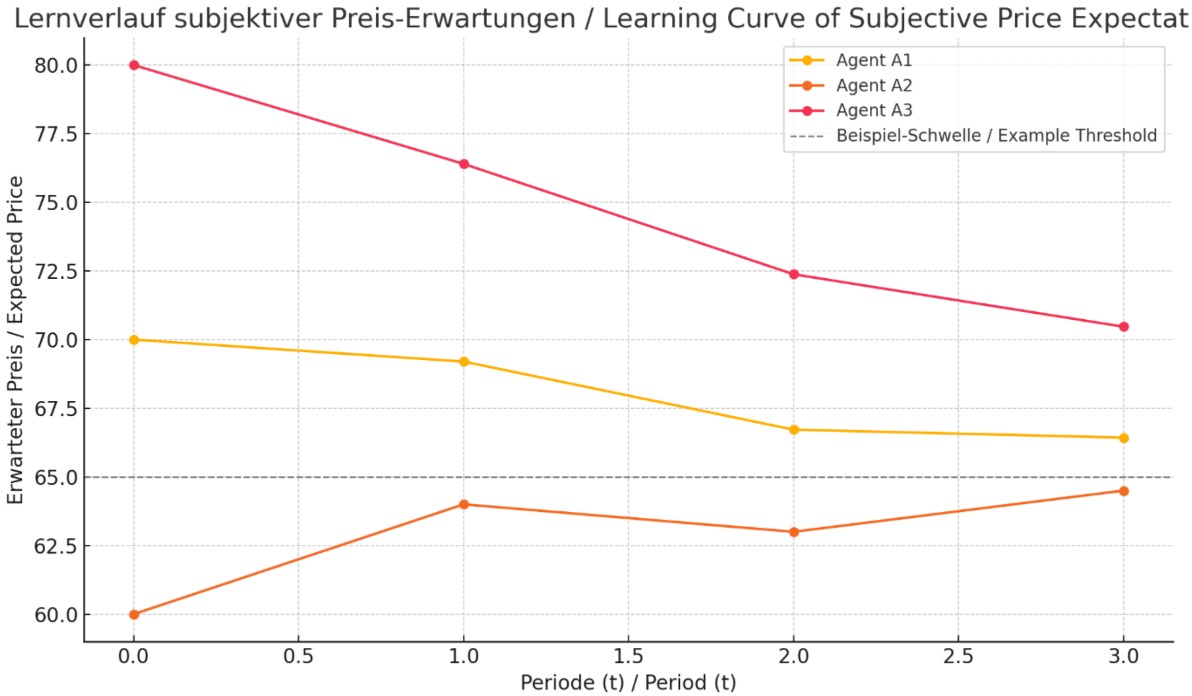
Figure 2: Learning process of subjective price expectations; Source: Own illustration according to Enrico Moch (2025), based on the Subjective Dynamic Decision Model (SDEM).



Statistical Robustness of Subjective Learning Dynamics and Theoretical Contrast with Bayesian Models

The simulation results demonstrate behavioural consistency and divergence across multiple agents with varied learning rates and thresholds. As illustrated in Figure 2, agents A1, A2, and A3 follow distinct expectation trajectories in response to the same market signals. These differences, especially A3's persistent overestimation and A1's rapid adjustment, highlight the robustness of path-dependent adaptation patterns that arise from subjective learning dynamics.

While the current results are based on a prototype application, the learning curves suggest internal consistency and reproducibility of behavioural types. Further trials with varied parameter settings yielded qualitatively similar dynamics, reinforcing the model's stability under stochastic fluctuations.

In contrast, Bayesian agents, guided by full probabilistic updating (Marwala et al., 2016), would converge more uniformly toward the empirical mean of observed prices. This would reduce the heterogeneity seen in Figure 2 but may also mask early behavioural divergences. The SDEM, by contrast, allows agents to act on limited information, personal thresholds, and heuristics. This results in faster, more flexible responses to market shifts, but also permits persistent deviations from "rational" expectations. The model thus captures both adaptive learning and behavioural specialization (Hey & Cross, 1985) that traditional equilibrium-based models tend to overlook.

FIELDS OF APPLICATION OF THE SDEM

The Subjective Dynamic Decision Model (SDEM) is particularly suitable for decision-making situations in which classic optimisation logics fail or no stable data is available. It unfolds its particular potential in complex, dynamic systems in which subjective perception, uncertainty and learning play a decisive role. The following areas of application show examples of how the model can be used in practice.

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In the energy sector, especially with the liberalisation of electricity and gas markets, supply companies are faced with the challenge of making supply and price decisions under uncertainty. Market participants have different information, evaluate it individually and react adaptively to market movements. Here, SDEM allows realistic modelling of decision paths based on subjective expectations about demand, regulation or price development. The simulation of such behaviour can help to better understand market stability and competition.

In the field of cyber security, the model enables the following: Mapping of dynamic threat situations in which the actors have incomplete and falsified information at their disposal. Security teams do not base their decisions on objective risk analyses, but on experience, current situation estimates and the enemy's presumed intentions. The SDEM provides a framework for simulating defensive and offensive strategies in a situation of uncertainty and thus promotes the formation of resilient security architectures.

Strategic information work in intelligence services is another field of application. In contrast to the previous models, decisions here are made in a context of deception, asymmetric information and intentional blurring of intentions. Classic game theory often fails here, as it assumes fixed utility functions and full rationality. With the help of SDEM, subjective estimates and their impact on operational decisions can be modelled, for example when evaluating the enemy's intentions or the conducting of covert operations.

Subjective decision-making is also playing an increasingly important role in *global supply chains*. In the face of geopolitical risks, ecological uncertainties and volatile markets, companies must constantly reassess how they select production locations, plan storage capacities or diversify suppliers. The SDEM enables modelling that integrates empirical knowledge, local information and strategic anticipation. Particularly under shock conditions, such as a pandemic or a sudden embargo, the model shows how companies can develop new routines and action strategies through learning processes.

Empirical case study: Location decision of two automobile manufacturers (SDEM)

A realistic example from the German automotive industry is used below to illustrate the Subjective Dynamic Decision Model (SDEM) in practice. Two companies, Manufacturer A and Manufacturer B, are faced with the challenge of making a location decision in an uncertain geopolitical and economic environment. The aim is to build a new plant in Europe in order to ensure long-term competitiveness in the transformation to electromobility.

Subjective decision state:

Both companies have different information, experience and assessments. While company A relies on market studies, existing supply chains and a geopolitical briefing, company B relies on expert networks, internal analyses and trade data. Based on these individual constellations, a subjective decision is made in each case:

$$S_t^A = (I_t^A, B_t^A, E_t^A), \quad S_t^B = (I_t^B, B_t^B, E_t^B)$$

A believes in the long-term advantages of Eastern European production locations, expects increasing subsidies in Hungary and sees logistical risks as manageable. B, on the other hand, is sceptical about south-eastern Europe, sees an energy bottleneck in Poland, but expects stable long-term development with the corresponding EU subsidies.

Heuristic decision logic:

Both companies apply subjective decision rules. A chooses the location if the expected cost advantage is at least ten per cent compared to the status quo. B only decides in the case of perceived investment security of over seventy per cent, measured on an internal expectation scale. This means that the same

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problem and external situation lead to different actions: A decides in favour of Hungary at an early stage, B hesitates with Poland.

Observation and learning:

After the first year of operation, the results are mixed. A is experiencing regulatory uncertainty in Hungary due to sudden changes in legislation. B recognises new support programmes for battery cell production and an improvement in the energy infrastructure in Poland. These observations (otio^i_toti) lead to an adjustment of the expectation component:

$$E^A_{t+1} = \alpha \cdot o^A_t + (1-\alpha) \cdot E^A_t, \quad E^B_{t+1} = \alpha \cdot o^B_t$$

e according to the learning rate α (e.g. 0.6 for A, 0.4 for B), the subjective state is updated. A will prioritise regulatory stability more highly in future, B is more willing to invest in Central Eastern European markets.

Significance for the SDEM:

This example illustrates how real decision-making in complex, uncertain contexts can be better represented by subjective, iterative models than by static optimisation. The SDEM not only enables a realistic description of strategic behaviour, but also opens up new perspectives for simulation-based scenario analyses and political policy advice in the context of industrial transformations.

Toward Empirical Validation

While the examples presented in this section reflect realistic and empirically informed decision contexts, they remain structured simulations or scenario-based reconstructions. The case study on automotive manufacturers, in particular, draws from typical decision logics observed in the industry, but does not rely on direct corporate disclosures or field experiments.

Future research will aim to validate the SDEM empirically through applied case studies, possibly in collaboration with industrial partners in the energy, mobility, and cybersecurity sectors. Such validation would allow the model to be calibrated with real-time decision data, offering greater predictive and diagnostic power in organizational settings. This step is critical to transforming the SDEM from a theoretical-simulation tool into a widely deployable framework for strategic planning under uncertainty.

In summary, it can be said that the SDEM shows its strength where classic optimisation logics fail because the world cannot be fully anticipated (Kay & King, 2020; Knight, 1921). It offers not only a theoretical framework for analysing decisions, but also a practical tool for simulating adaptive behaviour patterns in realistic contexts

DISCUSSION

The Subjective Dynamic Decision Model (SDEM) represents a paradigm shift in the modelling of strategic decision-making processes. It shifts the focus from static rationality and equilibrium concepts (Basov, 2004; Bayraktar et al., 2020) to dynamics, subjectivity and the ability to learn (Gonzalez et al., 2017). This perspective allows a more realistic description of many complex contexts in which classical models with deterministic or stochastic parameters fail. A key advantage of the SDEM is its ability to be connected to different disciplinary issues.

Economic, safety-relevant and logistical scenarios can be modelled in equal measure without the need for a complete level of information. This allows the modelling of deception, error perception and evolutionary strategy development. At the same time, the SDEM poses conceptual challenges. As it is based on subjective expectations and unverifiable internal states, classical mathematical validation is only possible to a limited extent (Cooke, 2017). The informative value of the model is therefore primarily derived from simulation-based comparative studies (Gintis, 2007) and its explanatory power for real behavioural patterns (Pellis et al., 2014).

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From a methodological point of view, it should be emphasised that the SDEM is not a closed model in the classical sense, but a framework concept for explorative modelling under epistemic uncertainty (Hüllermeier & Waegeman, 2021). Its strength lies in its openness to individual contexts, heuristics and learning processes. The model contributes to overcoming the dichotomy between rational choice and behavioural economics (Kahneman, 2011) by making subjective rationality systematically integrable. It is therefore not only suitable for describing real decision-making processes, but also for developing innovative, adaptive strategies in practice.

Both results from the simulation and the empirical case study support the main assumptions of the SDEM. In the energy market scenario, both players followed learning curves characterized by high uncertainty at the beginning (Castellini et al., 2021), resulting in risk-averse behavior followed by subjectively heuristic specialization based on feedback (Kimbrough, 2010). The fact that both players learned in this way supports the assumption that the subjective, heuristic-driven updating process that we have assumed in SDEM can be a reasonable model for strategic adaptation under uncertainty in practice. Furthermore, the different specializations by the two players show how individual belief structures and expectation updates drive different outcomes, a characteristic that is frequently neglected in standard models (Matli & Phurutsi, 2023; Dricu et al., 2023).

The empirical case study of automotive manufacturers showed how subjective perception and learning play a central role in automotive manufacturers' strategic choices under geopolitical and economic uncertainty (Struckell et al., 2022; Nygaard, 2022; Monye et al., 2023). The results indicate that the outcomes of SDEM are pertinent for real-world decision-making environments including dynamic, distributed, and inadequate knowledge sources. Among other fields, like energy supply management, cybersecurity risk assessment, strategic intelligence, and global supply chain resilience, the findings further demonstrate that SDEM can be a significant analytical tool.

Limitations of the ModelA key feature of the model is simulation-based validation, which is a powerful method for analysing the impact of subjective perception and uncertain environments on decision-making. These simulations provide valuable insights into how the SDEM works in different scenarios, such as energy supply and cybersecurity. However, it is important to emphasise that the generalisability of the results to real, empirical data remains context-dependent. The theoretical results and the simulations provide valuable indications of possible decision patterns, but the specific results in different real-world settings might differ from the modelled scenarios. It is recommended to further validate and adapt the model in future empirical studies to verify its applicability and robustness under real-life conditions. Due to the abstract and heuristic nature of the model, empirical validations and comparisons with real data are necessary to further refine the model. Future work should focus on testing the SDEM in various practical applications to confirm its predictive power and adaptability in different environments.

LIMITATIONS

Several limitations exist for this work, although the Subjective Dynamic Decision Model (SDEM) offers a general representation of strategic behaviour under uncertainty. First, the use of simulation-based validation limits empirical generalizability (Al-Ubaydli & List, 2012). In practice, the decision context may include other factors that were not considered in the model. Second, the assumptions made regarding heuristic decision making and subjectively updating beliefs are realistic; however, this makes formal mathematical validation more difficult (Gilbert-Saad et al., 2023). Third, the prototype applications have taken place in particular domains (energy markets, automotive industry) and may need to be adapted for other settings. Future work should seek

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to empirically test the model in a variety of settings and refine heuristic formulations through case-based work. A further limitation lies in the operationalization of subjective states such as individual beliefs, conviction levels, and expectations (Czeglédi, 2020; Tuckett & Nikolic, 2017). In the simulation, these were approximated using predefined parameters (e.g., learning rates, threshold values, and initial priors). However, in practical applications, capturing such states requires either self-reported assessments (via interviews or surveys), behavioral proxies (e.g., investment timing, reaction to shocks), or cognitive elicitation techniques. These methods introduce new layers of subjectivity and measurement noise. Future studies should therefore explore standardized ways to quantify subjective decision states across sectors to enhance the empirical applicability of the SDEM.

THEORETICAL AND PRACTICAL IMPLICATIONS

Theoretical Implications:

The Subjective Dynamic Decision Model (SDEM) contributes to decision theory by introducing a formal structure that places subjective perception, heuristic reasoning, and iterative learning at the center of decision-making under radical uncertainty. By bridging bounded rationality (Simon, 1955) with adaptive agent-based modelling (Epstein, 2006; Tesfatsion & Judd, 2006), SDEM offers a conceptual alternative to classic rational choice models and dynamic programming approaches (He, 2021; Klibanoff et al., 2005). It systematically integrates learning from feedback and distortion into decision processes, providing a dynamic, subject-centered model capable of capturing evolving behavioural strategies. Moreover, it contributes to epistemological debates by offering a structured method for modelling decision-making without assuming complete information, perfect rationality, or fixed expectations, expanding the theoretical landscape beyond existing models of ambiguity and risk.

Practical Implications:

In practice, SDEM allows for more accurate simulation and analysis of strategic behaviour in uncertain and volatile conditions. It is pertinent in fields including energy market trends, reactions to cybersecurity concerns, supply chain risk management, and intelligence agencies, where players must learn to live with uncertainty. Policymakers and strategists can apply the results from SDEM-based simulations to understand the impact of subjective learning and misperceptions on market outcomes, survival, and competitive behaviour. Furthermore, the approach offers a framework for adaptive scenario analysis to help companies create flexible plans following geopolitical shocks, legal mistakes, or technology discontinuities. Emphasizing subjective adaptation, SDEM at last provides a means to enable one to better understand strategic adaptation in action.

Practical application of the SDEM

The SDEM model is not only theoretically relevant, but also offers practical applications in a variety of areas. The agent-based simulation makes it possible to model strategic decisions in uncertain environments such as the energy industry, cybersecurity and global supply chains. The model shows its strengths particularly in areas where traditional optimisation approaches fail, such as modern energy supply or strategic information work. Here, adaptive decision-making under uncertainty is simulated, which provides valuable insights into the development of resilience and competitive strategies in dynamic systems. The model could also be relevant in political decision-making processes, as it helps to understand the impact of uncertain and changing political conditions on decision-making. With the help of simulation-based scenarios, the model can be used to conduct future-oriented analyses that enable political decision-makers to react flexibly to geopolitical uncertainties, economic crises or environmental challenges.

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Example of practical application

A possible example of the application of the SDEM could be the modelling of decisions in global supply chains. Given the uncertainty surrounding geopolitical risks, market changes and natural disasters, companies need to regularly adapt their supply chain strategies. The SDEM could be used here to investigate how adaptive strategies are developed under uncertainty and which long-term learning processes lead to more robust and resilient supply chains.

CONCLUSION AND OUTLOOK

The Subjective Dynamic Decision Model (SDEM) provides a new perspective on strategic decision-making in environments characterised by uncertainty, dynamics and interpretation. By integrating subjective states, heuristic decision-making mechanisms and iterative learning processes, it represents a realistic alternative to classic models. The theoretical and simulation-based analyses to date show that the model is not only suitable for explaining existing behaviour, but also for inspiring new strategies. Especially in contexts with asymmetric information, unclear target variables or changing framework conditions, SDEM offers a flexible and connectable analysis approach. Several research perspectives open up for the future: Empirical validation through case studies, the further development of specific heuristic functions and integration into existing decision-making systems and simulation tools. In addition, the model could contribute to the development of learning algorithms based on subjective evaluation rather than exact optimisation. While promising, these applications require careful operationalisation of subjective states and a stronger empirical foundation. Future implementation efforts must address challenges such as quantifying beliefs and expectations, integrating domain-specific heuristics, and testing the model's performance in complex real-world environments.

Rather than claiming universality, the SDEM should be seen as a complementary tool that expands existing modelling frameworks by explicitly incorporating subjectivity and learning. This positions it as a valuable contribution to the methodological toolkit for decision research under uncertainty.

SDEM is exemplary for an epistemologically reflected approach to decision modelling and represents an invitation not to simplify complex reality, but to make it methodologically productive in its uncertainty. In addition to these epistemological perspectives, the model also offers concrete approaches for practical implementation in organisations and decision-making processes.

Practical relevance and implementation

Beyond its theoretical scope, the Subjective Dynamic Decision Model (SDEM) also has direct practical relevance. Organisations, political decision-makers and research institutions can benefit from the application of simulation-based, subjective decision models in a number of ways.

Implementation in companies:

The SDEM can be integrated into existing decision support systems, such as agent-based simulation software or modular extensions to business intelligence tools. In areas such as risk and investment management, the model can help to systematically analyse different expectation horizons and learning behaviour. However, successful implementation requires the careful translation of qualitative decision rules into formal parameters, and alignment with available behavioural or contextual data. Available tools:

The implementation can be carried out on established platforms such as Python (with libraries such as NumPy, pandas, Mesa) or simulation environments such as NetLogo. These enable intuitive modelling of individual actors with subjective states, adaptive behaviour and non-linear feedback.

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Use of simulation-based scenarios:

By using repeatable and variable scenarios, uncertainties can not only be mapped, but also actively explored. This creates a deeper understanding of path-dependent developments, robust strategies and responsive organisational structures in volatile environments. Particularly in strategic planning and political consulting, the model opens up access to the simulation of plausible future scenarios based on real decision-making logic.

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